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Illiquid Trades on Insurance Companies in Financial Crisis

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Abstract

The bankrupt of Lehman Brothers in 2008 triggered a series of panic selling on stocks, especially the stock of insurance companies, which makes the illiquidity of stock markets. Therefore, in this study we examine the relation between insurance companies' stock liquidity and return, and market makers' behavior when market is illiquid. We find that before financial crisis market makers' inventory level of stock is not sufficient, hence, they have to adjust quote price when they confront order imbalances. Nevertheless, the impacts of order imbalances become insignificant after crisis. Market makers do not adjust quote price as much as to fully reflect the information because they need time to assert that the imbalances contain information before financial crisis. Nevertheless, they fully adjust quote price simultaneously when they confront large order imbalance after financial crisis, because they consider that large order imbalances are definitely informed trading when market is illiquid. Connection between order imbalances and price volatility is low. It means that market makers have great ability to stable price volatility when facing the unexpected shocks. Market of insurance companies has less liquidity after financial crisis. While the market is illiquid after crisis, investors do not require significant higher liquidity premium.

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1 Introduction

The bankrupt declaration of Lehman Brothers in September 15, 2008 triggered a series of panic selling on stocks, especially the stock of insurance companies, which makes the illiquidity of stock markets. Therefore, our purpose is to examine the relation between stock liquidity and return, and market makers' behavior when market is illiquid. Besides, we attempt to find a trading strategy to see whether we can make excess return. By doing this, we can investigate the liquidity premium issue.

There have been a lot of researchers elaborate on liquidity issue. Brennan, Jegadeesh and Swaminathan (1993) find the returns on portfolios of firms followed by lots of analysts tend to lead those of firms followed by fewer analysts, even when the firms are of approximately the same size. Brennan and Subrahmanyam (1995) further analyze the relation between the number of analysts following a firm and the estimated adverse selection cost of transacting in the firm's security. They find that more analysts following a firm tend to reduce the adverse selection costs based on the Kyle (1985) notion of market depth. From previous researches, researchers use quoted bid-ask spread to measure illiquidity. However, they find the quoted bid-ask spread is a noisy measure of illiquidity. Therefore, Brennan and Subrahmanyam (1996) use intraday transaction data to estimate measures of illiquidity and adjust risk by Fama and French (1993) factors. They use these data to investigate the relation between monthly stock returns and illiquidity. They find that the relation between required rates of return and the measures of illiquidity they used is quite significant.

Brennan, Chordia and Subrahmanyam (1998) extend the model and find evidence of size, return momentum, and book-to-market effects, together with a significant and negative relation between returns and trading volume. Jacoby, Fowler and Gottesman (2000) examine the relationship between the expected return and the future spread cost within the CAPM framework. The result shows the relationship is positive and convex. Amihud (2002) shows that effect of illiquidity is much powerful on small firms stocks, implying an explanation for the small firm effects. Chordia (2002) finds that market order imbalances, defined as aggregated daily market purchase order minus sell order, are positive autocorrelated. Chordia, Roll and Subrahmanyam (2002) find that order imbalances increase following market decline and vice versa, which means that investors are contrarians in aggregate. Moreover, they find order imbalances in either direction, excess buy or sell orders, reduce liquidity.

P´astor and Stambaugh (2003) investigate whether market-wide liquidity is a state variable important for asset pricing. They find that expected stock returns are related cross-sectional to the sensitivities of returns to fluctuations in aggregate liquidity. Baker and Stein (2004) document that unusually high liquidity is an indication of the fact that the market is currently dominated by these irrational investors, and hence is overvalued. Eisfeldt (2004) finds that higher productivity leads to increased liquidity. Moreover, liquidity enlarges the effects of changes in productivity on investment and volume. High productivity implies that investors initiate a larger scale risky project which increases the riskiness of their incomes. Riskier incomes induce more sales of claims to high-quality projects, causing the increase of liquidity. Acharya and Pedersen (2005) shows how a persistent negative shock to a security's liquidity results in low contemporaneous returns and high predicted future returns. The model offers a simple, combined framework for understanding the various channels through which liquidity risk may affect asset prices.

Chordia, Huh and Subrahmanyam (2005) show that past return is the most significant predictor of stock turnover; forecast dispersion and systematic risk also play important roles in predicting the cross-section of expected trading activity. Stocks that have performed well experience aggressive buying pressure in the subsequent year, which points to the presence of momentum investing. Johnson (2005) computes the function for some tractable example models and uncovers a rich variety of predictions about liquidity dynamics that appear consistent with both the levels and covariations observed in the data. The results have important implications for the pricing and hedging of liquidity risk. Chordia, Huh and Subrahmanyam (2009) find that theory-based estimates of illiquidity are priced in the cross-section of expected stock returns, even after accounting for risk factors, firm characteristics known to influence returns, and other illiquidity proxies prevalent in the literature. Hanselaar, Stulz, and Van Dijk (2018) show that changes in equity issuance are positively related to lagged changes in aggregate local stock market liquidity. Wu (2018) find that insiders from liquid firms also trade more aggressively after coverage reductions.

We can find most of previous studies about liquidity in asset pricing show that liquidity does play an important role in asset pricing. In addition, some researches indicate that we can use order imbalances to investigate the behavior of informed traders and see if there exists information asymmetry. Therefore, we want to use order imbalance as an indicator to investigate the relation among the daily stock return and volatility. Besides, we apply the proxy which Chordia, Huh and Subrahmanyam (2009) used as the measure of illiquidity.

Our study proceeds as follows. First, we obtain our raw data from NYSE TAQ, and then apply the Lee and Ready (1991) trade assignment algorithm to determine the direction of each order. Then, we compiled these order data into daily order imbalances. Second, we used multiple Ordinary Least Squares regression to test both contemporaneous as well as lagged relations between returns and order imbalances. Third, we apply the GARCH (1, 1) model and extended it to incorporate the effects of order imbalance to the stock returns. In particular, we added the regression effects of order imbalance to both stock returns and volatility. Forth, we calculate the liquidity measurement proxy proposed by Chordia, Huh, and Subrahmanya (2009) to determine the liquidity level of these two periods. Finally, we form a trading strategy based on order imbalances to test whether we can make excess return.

Our result shows that AIG is the only insurance company of which the coefficient of lagged-one imbalance is positive and significant at one percent significance level. However, the coefficient turns to be insignificant after crisis. In addition, we find that both contemporaneous and lagged-one order imbalances are positive correlated with current returns before crisis. Nevertheless, only contemporaneous order imbalances are positive correlated with current returns after crisis. We also find that the relation between price volatility and order imbalance is not as significant as we expected. Besides, the liquidity measurement proxy proves that the market is less liquid after financial crisis. Last but not least, the result of our trading strategy shows that investors do not require significant higher liquidity premium even market is quite illiquid during the period after financial crisis.

The remainder of this paper proceeds as follows. Section 2 describes the data and methodology we used in our study. Section 3 presents the empirical results based on the methodology, and section 4 provide conclusion.

2 Data and Methodology

2.1 The Data

2.1.1 Data Sources

The main purpose of our study is to investigate how illiquidity affects the stock returns of insurance company during financial crisis. First, we select ten U.S. insurance company listed on NYSE for their high liquidity, large market capitalization and huge daily transaction volume. We acquire our data from NYSE TAQ (New York Stock Exchange Trades and Quotes) and the period is from July 1, 2008 to November 30, 2008, namely two and half months before and after Lehman Brothers bankruptcy which is on September 17, 2008. We use the database to get the intraday transactions data that includes bid and ask quotes and trading prices as well as trading size. Furthermore, we only use the trading data within market time (9:30AM to 4:00PM), and trades before and after the period will be ignored since we only focus on trading behavior during market time.

2.1.2 Data Processing Methods

Stock are included or excluded in our samples depending on the following criteria: First, the top ten insurance companies listed in NYSE based on liquidity, market capitalization and size concern. Second, to avoid noise trading, we delete transaction data within the first 90 seconds after the market opens. Third, quotes established and transactions traded before the opening or after the close are excluded.

After selecting the sample that meets the criteria mentioned above, we start to calculate the daily order imbalances for each sample. We use the Lee and Ready (1991) trade assignment algorithm to assign each transaction to either buyer-initiated or seller-initiated. The Lee and Ready test involves two-step approach. The first step is quote test. If the actual transaction price is greater (smaller) than the mid-point of the bid and ask price, the trade is classified as buyer-initiated (seller-initiated). If the trade price is exactly at the midpoint of the bid and ask price, the tick test is executed.

The trade is classified as buyer-initiated if the last non-zero price change is positive, and vice versa. Then, we define order imbalance as the number of buyer-initiated trades minus the number of seller-initiated trades in light of Chordia and Subrahmanyam (2002).

2.1.3 Descriptive Statistics

Based on the criteria mentioned above, we select ten stocks of insurance company in the United States, which are ACE Limited (ACE), American International Group (AIG), Chubb Corporation (CB), Loews Corporation (L), MetLife (MET), Manulife Financial Corporation (MFC), Prudential Financial (PRU), Prudential Public Limited Company (PUK), Sun Life Financial (SLF), and The Travelers Companies (TRV) as our sample data. The basic information and descriptive statistics of our sample stocks are presented in Table 1. With regard to the entire period of our sample, the mean of open-to-close return is -0.33%, with a median of -0.26%. The standard deviation of return is 7.72%, with a maximum return of 43.12% and a minimum return of -60.79%. The skewness of daily return is -0.1825 and the kurtosis is 8.3405. With regard to the period before crisis, the mean of open-to-close return is -0.22%, with a median of -0.05%. The standard deviation of return is 4.56%, with a maximum return of 13.46% and a minimum of -60.79%. The skewness of daily return is -5.2781 and the kurtosis is 63.5196. With regard to the period after crisis, the mean of open-to-close return is -0.46%, with a median of -0.73%. The standard deviation of return is 9.96%, with a maximum return of 43.12% and a minimum return of -45.33%. The skewness of daily return is 0.3738 and the kurtosis is 2.3652.

Table 1: Descriptive Statistics of Selected Stocks' Daily Return

Mean	Median	Standard Deviation	Maximum	Minimum	Skewness	Kurtosis
Panel A: All Time Period						
-0.33%	-0.26%	0.0772	43.12%	-60.79%	-0.1825	8.3405
Panel B: Pre Crisis						
-0.22%	-0.05%	0.0456	13.46%	-60.79%	-5.2781	63.5196
Panel C: After Crisis						
-0.46%	-0.73%	0.0996	43.12%	-45.33%	0.3738	2.3652

2.2 Methodology

2.2.1 Unconditional Lagged Return-Order Imbalances OLS Model

In order to examine the prediction power of lagged order imbalances which is indicated by Chorda and Subrahmanya (2004), we use multi-regression model to test the impact of five lagged order imbalances on current stock returns for the period before and after financial crisis.

The linear regression model is:

$$R_{i,t} = \alpha_0 + \alpha_1 OI_{i,t-1} + \alpha_2 OI_{i,t-2} + \alpha_3 OI_{i,t-3} + \alpha_4 OI_{i,t-4} + \alpha_5 OI_{i,t-5} + \varepsilon_t \tag{1}$$

where $R_{i,t}$ is the current stock return of seven foreign investment banks, and is defined as $\ln(P_t/P_{t-1})$; i = 1,2,3,4,5,6, and 7, which represents BCS, CS, DB, HBC, RY, UBS, and NMR, respectively. $OI_{i,t}$ is the lagged order imbalances at time t of the foreign investment bank i. ε_t is the residual of the stock return.

If the result shows that the coefficients on the independent variables are significant, we can infer that the order imbalances have predictive power on future intraday returns. Then, we can develop some profitable trading strategies by using order imbalances as a useful indicator, and we can examine market efficiency by testing the statistical significance of trading profit. Besides, we can calculate the measure of liquidity by dividing $\alpha 1$ by average price.

2.2.2 Conditional Contemporaneous Return-Order Imbalances OLS Model

In this section, we use a multiple-regression model to examine the impact of contemporaneous and four lagged order imbalances on current stock returns for the period before and after financial crisis.

The linear regression model is:

$$R_{i,t} = \alpha_0 + \alpha_1 OI_{i,t} + \alpha_2 OI_{i,t-1} + \alpha_3 OI_{i,t-2} + \alpha_4 OI_{i,t-3} + \alpha_5 OI_{i,t-4} + \varepsilon_t \tag{2}$$

Where $R_{i,t}$ is the current stock return of seven foreign investment banks, and is defined as $\ln(P_t/P_{t-1})$; i = 1,2,3,4,5,6, and 7, which represents BCS, CS, DB, HBC, RY, UBS, and NMR, respectively. $OI_{i,t}$ is the contemporaneous and lagged order imbalances at time t of the foreign investment bank i. $\varepsilon_{i,t}$ is the residual of the stock return.

By analyzing t-values of coefficients of independent variables, we can find if there exist significant impacts of each independent variable on current stock returns. According to Chordia and Subrahmanyam (2004), we expect a positive relation between contemporaneous imbalances and current returns, and a negative relation between current returns and lagged order imbalances.

2.2.3 Dynamic Return-Order Imbalance GARCH (1, 1) Model

Since the variances of the stock prices time series of the samples are not as constant as what OLS model assumes to be, we adopt GARCH (1,1) model which can catch the time-variant property of price series more precisely to solve the weakness of the assumption of OLS regression model We use the model to examine the dynamic relation between returns and order imbalances for both before and after financial crisis periods:

$$\mathbf{h}_t = A + \mathbf{B}\, h_{t-1} + \mathbf{C}\, \varepsilon^2_{t-1} \tag{3}$$

where R_t is the return at time t, and is defined as ln (Pt)-ln(Pt-1), OI_t denotes the explanatory variable of order imbalance, β is the coefficient describing the impact of order imbalance on stock returns, ε_t is the residual value of the stock return at time t, h_t is the conditional variance at time t, Ω_{t-1} is the information set in at time t-1.

By observing the significance of coefficient B, we can recognize whether the GARCH (1,1) model is able to capture the time variant property. Besides, we can see if there exists significant effect of the order imbalances on contemporaneous returns by observing β.

2.2.4 Dynamic Volatility-Order Imbalance GARCH (1, 1) Model

We adopt GARCH (1, 1) to investigate the dynamic relation between order imbalances and volatility in this section:

$$R_t = \alpha + \boldsymbol{\varepsilon}_t$$

$$\boldsymbol{\varepsilon}_t \mid \boldsymbol{\Omega}_t \sim N(0, \mathbf{h}_t)$$

$$\mathbf{h}_t = A + \mathbf{B}\, h_{t-1} + \mathbf{C}\, \varepsilon^2_{t-1} + \gamma\, \mathbf{OI}_t \tag{4}$$

where R_t is the return at time t, and is defined as ln (Pt)-ln(Pt-1), OI_t denotes the explanatory variable of order imbalance, ε_t is the residual value of the stock return at time t, h_t is the conditional variance at time t, Ω_{t-1} is the information set in at time t, γ is the coefficient describing the impact of the order imbalance on volatility of the return.

We can use the coefficient and t-statistics of γ to examine the relation between order imbalance and volatility.

2.2.5 Liquidity Measurement

In this part, we use the results of our pervious unconditional OLS model to test market liquidity. We adopt Chordia, Huh and Subrahmanyam (2009) liquidity estimation model to measure market liquidity in two different time intervals; before and after crisis periods.

The liquidity measure is:

$$L = \frac{|\lambda_i|}{P_i} \tag{5}$$

Where λ_i is the coefficient of lag one order imbalance in unconditional return-order imbalance OLS model at period *I*, P_i is the average market close prices of samples in unconditional return-order imbalance OLS model at period *i*.

The liquidity measure L is the effect of order imbalances on stock returns adjusted for stock price. As we know that the higher the liquidity the influence of order imbalances on stock returns should be lower, consequently, a larger L indicates a lower liquidity market condition.

3 Empirical Results

3.1 Unconditional Lagged Return-Order Imbalances Relation

In this section, we use a multiple-regression model to investigate the unconditional lagged return-order imbalances OLS relation with five lagged order imbalances. We want to test if lagged order imbalances bear a positive predictive relation to current returns of insurance companies.

Panel A of Table 2 presents the summary before financial crisis and it shows that the average coefficient of lagged-one order imbalance is positive and has a value of 5.82E-07, and the percentage of lagged-one order imbalances is higher than 50% which is 80.0%. At 5% significant level, the ratio of positive and significant coefficients of lagged-one order imbalance is 10.0%, and the ratio of negative and significant coefficient is 10.0%. Panel B of Table 2 shows that the average of the coefficients of lagged-one order imbalance is positive and has a value of 4.10E-06, and the percentage of lagged-one order imbalances is higher than 50% which is 70.0%. At 5% significant level, the ratio of positive and significant coefficients of lagged-one order imbalance is 0.0%, and the ratio of negative and significant coefficient is 0.0%.

Table 2: Unconditional Lagged Return-Order Imbalance OLS Relation

Panel A: Pre-Crisis Period

	Average Coefficient	positive	Positive and Significant	Negative and Significant
OIt-1	5.82E-07	80.00%	10.00%	10.00%
OIt-2	-1.17E-06	10.00%	0.00%	0.00%
OIt-3	1.77E-06	80.00%	20.00%	0.00%
OIt-4	7.30E-06	90.00%	20.00%	0.00%
OIt-5	2.29E-06	60.00%	0.00%	0.00%

Panel B: After-Crisis Period

	Average Coefficient	positive	Positive and Significant	Negative and Significant
OIt-1	4.10E-06	70.00%	0.00%	0.00%
OIt-2	1.79E-06	40.00%	10.00%	0.00%
OIt-3	1.12E-05	60.00%	0.00%	0.00%
OIt-4	9.19E-06	20.00%	0.00%	10.00%
OIt-5	-1.24E-05	20.00%	0.00%	0.00%

We further examine the results of the company which the coefficient of lagged-one order imbalances is significant. We find that the coefficient of lagged-one imbalance of AIG is positive and significant at one percent significance level before crisis. However, the coefficient is not significant after crisis. It means that before financial crisis market makers do not prepare enough inventory of AIG's stock, hence, they have to adjust quote price when they confront order imbalances. Nevertheless, the impacts of order imbalances become insignificant after crisis. There are two possible reasons to explain this phenomenon. 1. Since AIG is one of the problem companies in financial crisis, market makers have already adjusted their ordinary inventory level to cease the possible large order imbalances to influence stock price. Therefore, large order imbalances turn to have no significant impacts after crisis. 2. The market is quite illiquid after crisis, so market makers could cease the effect of order imbalances easily by just holding the same level of inventory.

3.2 Conditional Contemporaneous Return-Order Imbalances Relation

We use a multiple-regression model explained by current returns, contemporaneous and four lagged order imbalances to examine the conditional lagged return-order imbalance OLS relation in this session.

Panel A of Table 3 presents the summary using overall data before financial crisis and it shows that the average of the coefficients of contemporaneous order imbalance is positive and has a value of 1.11E-05, and the percentage of contemporaneous order imbalances is higher than 50% which is 100.0%. At 5% significant level, the ratio of positive and significant coefficients of contemporaneous order imbalance is 50.0%, and the ratio of negative and significant coefficient is 0.0%.

Table 3: Conditional Lagged Return-Order Imbalance OLS Relation

Panel A: Pre-Crisis Period

	Average Coefficient	positive	Positive and Significant	Negative and Significant
OIt	1.11E-05	100.00%	50.00%	0.00%
OIt-1	-1.20E-06	50.00%	10.00%	10.00%
OIt-2	-1.00E-06	20.00%	0.00%	20.00%
OIt-3	9.36E-07	80.00%	20.00%	0.00%
OIt-4	6.53E-06	90.00%	0.00%	0.00%

Panel B: After-Crisis Period

	Average Coefficient	positive	Positive and Significant	Negative and Significant

OIt	2.47E-05	100.00%	50.00%	0.00%
OIt-1	1.10E-06	50.00%	10.00%	0.00%
OIt-2	1.76E-06	40.00%	0.00%	0.00%
OIt-3	9.49E-06	60.00%	0.00%	0.00%
OIt-4	9.67E-06	20.00%	0.00%	20.00%

Panel B of Table 3 shows that the average of the coefficients of contemporaneous order imbalance is positive and has a value of 2.47E-05, and the percentage of contemporaneous order imbalances is higher than 50% which is 100.0%. At 5% significant level, the ratio of positive and significant coefficients of contemporaneous order imbalance is 50.0% and the ratio of negative and significant coefficient is 0.0%.

The empirical result of our study shows that the coefficients of contemporaneous order imbalances are significantly positive at one percent significant level for both periods. The coefficients of lagged-one imbalances are also positive at one percent significant level before crisis but they become insignificant after crisis. The contemporaneous relation between imbalances and returns is in line with both inventory and asymmetric information effects of price formation. When market makers confront large order imbalances before crisis, they interpret it as informed trading and adjust quote price immediately. However, they do not adjust quote price as much as to fully reflect the information because they need time to assert that the imbalances contain information. Since imbalances are serially correlated, market makers will further adjust quote price when they confront another large order imbalance in the following period to fully reflect information. This is the reason why the coefficients of both contemporaneous and lagged imbalances are positive and significant before crisis. Nevertheless, the coefficient of lagged imbalances turns to be insignificant after crisis. It means that when market makers confront large order imbalance after crisis, they fully adjust quote price in the same time because they consider that large order imbalances are definitely informed trading when market is illiquid.

3.3 Dynamic Return -Order Imbalance GARCH (1, 1) Relation

From previous researches, we know that the stock prices are autocorrelated and the variances of the samples are not as constant as what OLS model assumes to be.

In order to release the assumption of OLS regression model and to enhance preciseness of our analysis, we adopt GARCH (1,1) model to catch the time-variant property of price series in Table 4.

Table 4: Dynamic Return-Order Imbalance GARCH(1,1) Relation

β	Average Coefficient	positive	Positive and Significant	Negative and Significant	Total
Pre Crisis	8.07E-06	90%	60%	0%	60%
After Crisis	2.28E-05	100%	50%	0%	50%

We get similar results comparing with conditional OLS regression model. Before financial crisis, the average of the coefficients of contemporaneous order imbalance is 8.07E-06, while after crisis, the average increases to 2.28E-05. The percentage of positive coefficients is 90% before crisis, and the percentage of positive coefficients is 100% after crisis. At the 5% significant level, the proportion of significantly positive β are 60% before crisis and 50% after crisis.

The general picture we got from GARCH (1,1) model is similar with OLS model, we still notice that the explaining power of order imbalance is different between GARCH (1,1) model and OLS regression model. This phenomenon can be explained as follows. When we apply OLS regression model, we assume the variance is constant over time, while this assumption is unrealistic because the stock price fluctuation is very volatile in real word. Therefore, we can get a more precise and reliable result after replacing OLS regression model with GARCH (1,1) model.

3.4 Dynamic Volatility -Order Imbalance GARCH (1, 1) Relation

In Table 5, we test the relation between price volatility and order imbalance which we expect the relation is positive, that is, large price volatility is accompanied by large order imbalance.

Table 5: Dynamic Volatility-Order Imbalance GARCH(1,1) Relation

γ	Average Coefficient	positive	Positive and Significant	Negative and Significant	Total
Pre Crisis	-9.00E-10	50%	20%	10%	30%
After Crisis	1.79E-06	30%	10%	0%	10%

The results show that the proportion of significantly positive or negative coefficients of order imbalances is not as large as we expect, that is, the order imbalance impact on volatility is not as strong as we expect. Before crisis, the average of the coefficients of order imbalance is -9.00E-08, whereas after crisis, the average is 1.79E-07. The percentage of positive coefficients is 50% before crisis, and the percentage of positive coefficients is 30% after crisis.

Besides, we find that before financial crisis, at 5% significant level, the percentage of positive and significant coefficients is 20% and 10% for negative one. After financial crisis, at 5% significant level, the percentage of positive and significant coefficients is 10% and 0% for negative one.

The low correlation between order imbalances and price volatility could be explained that market makers have good control on insurance companies' price volatility, that is, market makers have good inventory adjustment mechanism. They don't need to adjust quote price largely to stabilize the market, thus investors can't influence the stock continuously.

3.5 Liquidity Measurement

In this section, we measure the differences of liquidity of insurance companies' stocks for both before and after financial crisis periods. We applied Chordia, Huh, and Subrahmanya (2009) liquidity measurement proxy to determine the liquidity level of these two periods. From Table 6, we show that before the financial crisis, the average of our price-scaled liquidity measure is 1.19E-8, whereas after the financial crisis the average of our price-scaled liquidity measure increases to 1.74E-7. The result indicates that the market of insurance companies have less liquidity after financial crisis, because the measurement proxy is higher which means the influence of order imbalances on stock returns is higher and market is at a lower liquidity condition.

Table 6: Liquidity Measurement

Time Interval	$\|\lambda\|/P$
Pre-crisis	1.19E-08
After -Crisis	1.74E-07

3.6 Trading Strategy

In this section, we try to form a trading strategy based on the sign of large order imbalances to test if the trading strategy can beat the market or not. Our strategy is as follows. We adopt 10% of the largest order imbalances for the periods of both before and after financial crisis. (ii) Buy the stock at the beginning of next trading day when the first corresponding large positive order imbalance appears. (iii) Sell the stock until the first corresponding large negative order imbalance appears. The detail results are presented in Panel A of Table 7 and hypothesis test in Panel B of Table 7. By performing our strategy during the period before the financial crisis, we can earn a daily return of -7.34%. We adopt one-tail t-test to see whether our trading strategy returns greater than zero. The t-values of test 1 reported in Panel B of Table 7, is -1.0879%. Even at the 10% significant level, there are no significant positive profits by executing the trading strategy.

Table 7: Trading Strategy

Panel A: Summary of Trading Strategy

Pre-Crisis	
Mean	-7.34%
Standard Deviation	0.213
After Crisis	
Mean	-26.40%
Standard Deviation	0.221

Panel B: Hypothesis Test of Return-Test

Test 1	
Pre-Crisis t-value	-1.0879
After-Crisis t-value	

	-3.7862***
Test 2	
Pre-Crisis t-value	-0.1541
After-Crisis t-value	0.118
Test 3	
t-value	0.1565

Apply the strategy during the period after the financial crisis; we can earn a daily return of -26.4% under stock-own situation. Likewise, we adopt the one-tail t-test to see whether the trading strategy return greater than zero. The t-values of test 1 reported in Panel B of Table 7 is -3.7862 under stock-own situation. From our empirical results, we find that our trading strategy based on order imbalances is not profitable, that is, we cannot earn positive returns by using the strategy for the two periods.

We also compare the holding period return with and without trading strategy by using paired-t test. The results of test 2 are presented in Panel B of Table 7. For the period of before financial crisis, we can find that the one-tail t-value is -0.1541 and the one-tail t-value is 0.1180 for the period after financial crisis. From the test results, we know that applying a strategy based on order imbalances would not result a better return compared with do nothing strategy for both periods which means we cannot beat market by executing the strategy.

Last but not least, in an attempt to provide a definitive answer as to whether such an order imbalances strategy gives a better performance after the financial crisis in which liquidity is scarce, we conducted another paired t-test on the two series (strategy return after crisis –strategy return before crisis). The result of test 3 is presented in Panel B of Table 7 and the t-value is 0.1565 which is not significant.

From the above results, we find our order imbalances strategy does not perform better than market. The reason could explain as follows. Since our samples are big insurance companies and the daily trading volume are huge, market makers of these companies put much more emphasis on the liquidity issue. Therefore, they tend to prepare sufficient stock inventories to prevent information trader from making excess returns. Moreover, from the test 3 results, we find our strategy returns are not significant difference between the two periods. It means while the market is quite illiquid after crisis, investors do not require significant higher liquidity premium.

4 Conclusion

There has been a lot of research concerned with liquidity issue since 1986. The main object of our study is to investigate how illiquidity affects market makers' behavior during financial crisis. We try to use order imbalance as an indicator to investigate the relation among the daily stock return, volatility and order imbalances of insurance companies during financial crisis.

We select major U.S. insurance company stocks listed on NYSE as sample for about half year and the period is from Jun 1st, 2008 to November 31th, 2008, with Lehman Brothers bankruptcy lying at the center.

First of all, in order to determine the prediction power of lagged order imbalances indicated by Chordia and Subrahmanya (2004), we apply a multiple-regression model explained by contemporaneous returns and five lagged order imbalances to examine the unconditional return- lagged order imbalance OLS relation. The result shows that only the coefficient of lagged-one imbalance of AIG is positive and significant at one percent significance level before financial crisis. However, the coefficient turns to be insignificant after crisis. The reason is that market makers adjust their stock inventory level to cease the impacts of large order imbalances after financial crisis or market makers could cease the effect of order imbalances easily by just holding the same level of inventory since market is quite illiquid after crisis.

Second, we apply a multiple-regression model explained by current returns, contemporaneous and four lagged order imbalances to examine the conditional return- lagged order imbalance OLS relation. The empirical result of our study shows that market makers do not adjust quote price as much as to fully reflect the information because they need time to assert that the imbalances contain information before financial crisis. Nevertheless, when they confront large order imbalance after financial crisis, they fully adjust quote price in the same time because they consider that large order imbalances are definitely informed trading when market is illiquid.

Next, In order to solve the weakness of the assumption of OLS regression model, we adopt GARCH (1,1) model to catch the time-variant property of price series. The general picture we got from GARCH (1,1) model is similar with OLS model, we still notice that the explaining power of order imbalance is different between GARCH (1,1) model and OLS regression model. We can get a more precise and reliable result after replacing OLS regression model with GARCH (1,1) model.

Moreover, the relation between price volatility and order imbalance is also an important issue in our study. We find that the proportion of significantly positive or negative coefficients of order imbalances is not as large as we expect. The low connection between order imbalances and price volatility could be explained that market makers have good control on insurance companies' price volatility. Possible explanation is that market makers have good inventory adjustment mechanism. Therefore, we can infer that market makers have great ability to stable price volatility when facing the unexpected shocks.

Then, we calculate the liquidity measurement proxy proposed by Chordia, Huh, and Subrahmanya (2009) to determine the liquidity level of these two periods. The result indicates that the market of insurance companies have less liquidity after financial crisis, because the measurement proxy is higher which means the influence of order imbalances on stock returns is higher and market is at a lower liquidity condition.

Finally, we form a trading strategy based on the sign of large order imbalances to test if the trading strategy can make preferable return. Our key result is that, we find our order imbalances strategy does not perform better than market. The reason is that our samples are big insurance companies and the daily trading volumes are huge, thus market makers of these companies put much more emphasis on the liquidity issue. Therefore, they tend to prepare sufficient stock inventories to prevent information trader from making excess returns. Moreover, from the test 3 results, we find our strategy returns are not significant difference between the two periods. It means while the market is quite illiquid after crisis, investors do not require significant higher liquidity premium.

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